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# RGB-D Segmentation of Poultry Entrails

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**Abstract.** This paper presents an approach for automatic visual inspection of chicken entrails in RGB-D data. The point cloud is first over-segmented into supervoxels based on color, spatial and geometric information. Color, position and texture features are extracted from each of the resulting supervoxels and passed to a Random Forest classifier, which classifies the supervoxels as either belonging to heart, lung, liver or misc. The dataset consists of 150 individual entrails, with 30 of these being reserved for evaluation. Segmentation performance is evaluated on a voxel-by-voxel basis, achieving an average Jaccard index of 61.5% across the four classes of organs. This is a 5.9% increase over the 58.1% achieved with features derived purely from 2D.

## 1 Introduction

As part of the quality control in poultry processing plants, the entrails of the slaughtered chickens are visually inspected e.g. to ensure that the organ extraction was successful. The entrails are extracted via the abdomen when the chickens are hanging upside down. Hearts and livers are sold separately for human consumption and it is therefore important that these organs are extracted undamaged. The lungs are not fit for consumption, but difficult to extract because they are intertwined with the chicken's ribs. Incomplete removal of entrails is a quality issue for chickens that are sold whole.

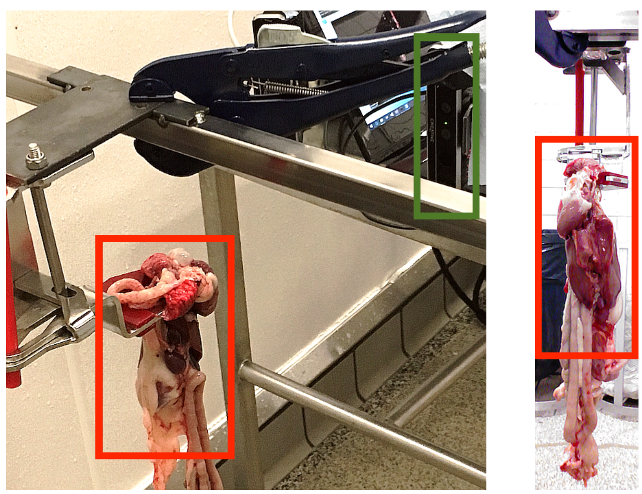
Inspection of these three organs is currently done manually, which is incredibly strenuous for the operator and limits the throughput of the entire processing plant. Assessing the quality of a set of entrails, calls for a segmentation method for the organs of interest. Entrails are non-rigid bodies, without straight lines and sharp edges, that only satisfies a weak spatial arrangement. In recent work by [1], a modified auto-context algorithm was developed to segment pig organs in RGB images. The modified algorithm uses an atlas of iteratively updated organ positions.

Quality control of organic material has often been done with hyper spectral imaging (HSI). HSI makes it possible to capture nuances in color, that are normally not visible with RGB cameras [2][3][6][9][14]. [13] was able to detect splenomegaly in poultry carcasses using ultra violet (UV) and color imaging. The use of UV aids in separating the spleen from the liver, which proved difficult in RGB images. [4] concluded that near infrared imaging can be used to access quality measures like tenderness and color of fresh beef. [7] discovered that two wavelengths, namely, $600nm$ and $720nm$, were optimal for detecting gallbladders attached to chicken livers.

Shape and depth information have been applied to other segmentation domains with good results. With the recent advances in available depth sensors, like Intel's RealSense and Microsoft's Kinect, this type of data has become very accessible. In this paper we show that state of the art 3D segmentation algorithms can be used for segmentation of chicken entrails in RGB-D data.

## 2 Setup

The dataset was captured using the Intel RealSense F200 3D camera. The chicken entrails were viewed frontally, from a distance of $35cm$, while placed in a hanger similar to the ones used on the production line. The entrails were taken directly from the production line and placed in the hanger, while retaining the same orientation as on the line. Figure 1 shows the setup used for data collection and the 3D camera's frontal view of the target.



(a) (b)

Fig. 1: (a) Hanger and 3D camera setup. (b) View from the camera. Red marks the target entrails and green marks the camera.

A total of 150 unique entrails were captured. The first 120 of these were reserved for training, while the remaining 30 were used in the evaluation. The calibration between RGB and D is given by the Intel RealSense SDK.

## 3 Segmentation Approach

Most existing research in segmentation of 3D scenes is focused on scenes with man-made objects, which exhibit straight lines and sharp edges. Two widely used datasets with these types of objects are the NYU V1 [12] and V2 [8] datasets. [15] is an example of recent work that addresses this type of data. They segment the point cloud into supervoxels and use a Random Forest (RF) classifier to initialize the unary potentials of a densely interconnected Conditional Random Field (CRF). In this paper we apply a similar framework to objects with significantly different characteristics. Our system differs from [15], by not including the CRF that is used for refining the labeling and by omitting the features that are specific to man-made object, as well as the features that utilize the orientation of the room. Figure 2 gives an overview of the pipeline for segmenting entrails into heart, liver, lung and misc. Figure 3a shows a labeled set of entrails.

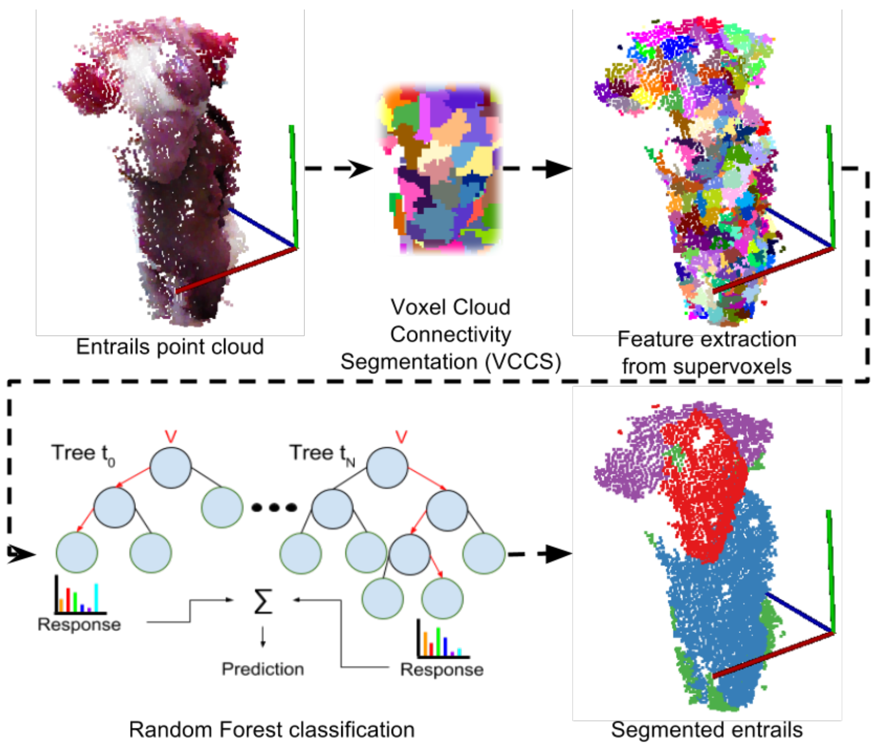



Fig. 2: Overview of the segmentation pipeline.

First the raw point cloud is cropped, leaving behind only the central region where the organs of interest are located. All of the points that remain in the point cloud are clustered into supervoxels based on spatial, color and geometric similarity. Color, position and texture features are extracted from each of the supervoxels and passed to a RF classifier, that labels each supervoxel as either heart, lung, liver or misc.

**Supervoxel segmentation** The purpose of over-segmentation is to reduce the amount of data and limit noise while preserving organ borders. We use the Voxel Cloud Connectivity Segmentation (VCCS) [10] supervoxel segmentation algorithm. VCCS produces the supervoxels by seeding the point cloud geometrically even. An iterative clustering algorithm groups voxels within $\sqrt{3}R_{seed}$ of each seed in a 39 dimensional space, based on spatial, color and geometric similarity. The importance of each feature type can be adjusted using weights. The 39 dimensional feature vectors consists of the CIELab channels, 3D point coordinate and the Fast Point Feature Histograms [11] descriptor.

**Random Forest** A label prediction for each supervoxel is given by a RF classifier. The RF consists of an ensemble of label distributions in the leaf nodes of the trees. The label distributions are created, during training, from the labels of training features that reaches particular leaf nodes when traversing through the RF. The dataset is skewed from the differences in organ sizes. Hence, priori probabilities that reflect the skewed distribution are assigned each class. Training is done, based on features extracted from supervoxels belonging to 120 sets of entrails. A feature vector and a label is passed for each supervoxel. Since the dataset is annotated on a voxel-by-voxel level, the label of a supervoxel is determined by majority vote on the voxel labels belonging to the given supervoxel. The feature vectors used for the RF consists of the mean and standard deviation of each CIELab channel and the supervoxel center coordinate, which brings the total of features to 9.

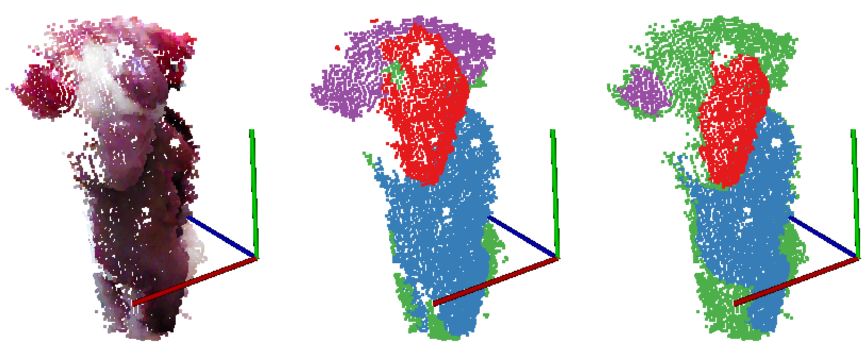
## 4 Evaluation

Since we have a manually annotated dataset we use a supervised evaluation approach, where the similarity between a labeled GT and the segmented output is quantified using the Jaccard Index. Figure 3(a) shows one example of a RGB 2D image that is used when annotating the entrails. Figure 3(b) shows the resulting annotation in 2D. Because of the uncertainty when annotating border regions, evaluation is done, using annotations with a "don't care" zone on the border of each class, as done in [5]. The annotation with the "don't care" zone can be seen in 3(c). Before the labels can be used for training and evaluation they are mapped onto the 3D point clouds, resulting in the labeled point cloud shown in Figure 3(d).


(a) (b) (c) (d)

Fig. 3: (a) 2D RGB image of entrails, with labeled organs. (b) Annotation in 2D. (c) Annotation with one pixel wide “don’t care” zone around each class. (d) Annotation mapped to 3D.

The final evaluation based on the 30 entrails in the test set, is done on a voxel-by-voxel basis. Every point belonging to a given supervoxel, thus inherits the supervoxel’s label. Finally, the quality of the segmentation can be evaluated by comparing the predicted labels in Figure 4(b) to the GT 4(c).



(a) (b) (c)

Fig. 4: (a) Original RGB point cloud. (b) Segmented point cloud. (c) GT point cloud with one voxel wide “don’t care” zone around each class. Green is misc., red is heart, blue is liver and purple is lung.

### 4.1 Results

Table 1 shows the voxel-wise Jaccard index for segmentation of the four classes. For the exclusively 2D based results, the features that are related to 3D are disabled. This is primarily impacting the clustering into supervoxel, as the geometric similarity is an important feature for that.

Table 1: Voxel-wise Jaccard index for the four classes.

| | Misc | Heart | Liver | Lung | Avg. |
|---|---|---|---|---|---|
| 2D | 62.9% | 44.4% | 76.8% | **48.4%** | 58.1% |
| 2D+3D | **66.1%** | **53.1%** | **79.2%** | 47.5% | **61.5%** |

It is clear from Figure 4 and Table 1 that the lung and heart are the most challenging organs to segment. The heart is small and much of it is covered by fat, which makes the color features much less effective. The lungs are also small and often occluded, therefore there is few voxels available for training and testing. Additionally, the lungs exhibit large variance in color, based on the amount of blood left in them. The segmentation example in Figure 4 indicates that the miss-classification of the misc. class as either heart or lung is the main issue. This might be addressed by modifying the weights on each class during training or by looking into the impact of the different features. In this case, it is likely that the spatial feature is too significant in the upper part of the point cloud.

## 5 Conclusion

We presented an approach for automatic visual inspection of chicken entrails and show that a segmentation algorithm previously used on man-made objects is able to function on vastly different objects. We achieve an average Jaccard index of 61.5% across the four organ classes. This is a 5.9% increase over the 58.1% achieved with features derived purely from 2D. Thus, the segmentation benefits from the additional information, that is available in RGB-D compared to RGB. Our use of 3D derived features is mainly limited to the segmentation into supervoxels. Therefore, improvements might lie in utilizing posterior optimizations as well as global and neighborhood features, many of which would be based on 3D.

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